#### RESEARCH ARTICLE

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# Analysis of air quality variability in Shanghai using AOD and API data in the recent decade

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Abstract We use the aerosol optical depth (AOD) measured by the moderate resolution imaging spectrometer (MODIS) onboard the Terra satellite, air pollution index (API) daily data measured by the Shanghai Environmental Monitoring Center (SEMC), and the ensemble empirical mode decomposition (EEMD) method to analyze the air quality variability in Shanghai in the recent decade. The results indicate that a trend with amplitude of 1.0 is a dominant component for the AOD variability in the recent decade. During the World Expo 2010, the average AOD level reduced 30% in comparison to the long-term trend. Two dominant annual components decreased 80% and 100%. This implies that the air quality in Shanghai was remarkably improved, and environmental initiatives and comprehensive actions for reducing air pollution are effective. AOD and API variability analysis results indicate that semi-annual and annual signals are dominant components implying that the monsoon weather is a dominant factor in modulating the AOD and API variability. The variability of AOD and API in selected districts located in both downtown and suburban areas shows similar trends; i.e., in 2000 the AOD began a monotonic increase, reached the maxima around 2006, then monotonically decreased to 2011 and from around 2006 the API started to decrease till 2011. This indicates that the air quality in the entire Shanghai area, whether urban or suburban areas, has remarkably been improved. The AOD improved degrees (IDS) in all the selected districts are  $(8.6\pm1.9)\%$ , and API IDS are  $(9.2\pm7.1)\%$ , ranging from a minimum value of 1.5% for Putuo District 25 30 35 40 45 50

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1) http://en.wikipedia.org/wiki/Shanghai

to a maximum value of 22% for Xuhui District.

Keywords air quality of Shanghai, MODIS AOD, API, EEMD method, World Expo 2010 25

### 1 Introduction

Shanghai is located at the Yangtze River Delta in the 30 middle portion of the Chinese coast and bounded on the east by the East China Sea as shown in Fig. 1. Its land area is 6340.5 km<sup>2</sup>. Shanghai is the largest city by population of China (over 23 million as of 2010), and also the largest city proper in the world<sup>1)</sup>. Following rapid development over 35 the last three decades, Shanghai has become a global city with influence in commerce, culture, finance, media, fashion, technology, and transport. Shanghai is a major financial center and the busiest container port in the world.

With the rapid development of the city, Shanghai suffers 40 heavy air pollution ([Kan and Chen, 2003a, b; Chen et al.,](#page-8-0) [2004](#page-8-0); [Zhang et al., 2006; Kan et al., 2007](#page-9-0); [Huang et al.,](#page-8-0) [2009](#page-8-0)). The urban air quality has been becoming a serious public concern. The megacity study shows that the concentrations of total suspended particulates (TSP) in 45 Shanghai were persistently above the World Health Organization (WHO) guidelines by a factor of as much as two or three [\(World Health Organization \(WHO\), 1987;](#page-9-0) [World Health Organization/United Nations Environment](#page-9-0) [Programme \(WHO/UNEP\), 1992, 1994; Mage et al., 1996;](#page-9-0) 50 [Wang et al., 2006](#page-9-0)). As reported by the Shanghai Environmental Bulletin, from 2001 to 2005, PM10 (particulate matter with the size  $< 10 \mu m$ ) was a major air pollutant on more than 80% of the days in the urban area of



Fig. 1 An ENVISAT ASAR image of Shanghai taken on May 31, 2010. The urban area is in a red rectangle. (ENVISAT ASAR data is provided by the European Space Agency.) 25 25

Shanghai [\(Kan and Chen, 2004;](#page-9-0) [Chan and Yao, 2008](#page-8-0)). Chen et al. [\(2006](#page-8-0)) estimated the emission of PM10 in 2005 was  $1.24 \times 10^5$  – $1.52 \times 10^5$  tons, and almost the same in 2006. Hao et al.  $(2011)$  used the tropospheric NO<sub>2</sub> column and CO concentration observations from satellite instruments, the Global Ozone Monitoring Experiment-2 (GOME-2) and Measurements of Pollution in the Troposphere (MOPITT), to evaluate the air quality in Shanghai 30 35

in 2010. They found a 12% reduction of CO concentration at 700 hPa and increases of  $NO<sub>2</sub>$  by 20%.

As pointed out by previous investigators, particulate matter (PM), or aerosol, is a general term used for a mixture of solid particles and liquid droplets found in the atmosphere ([Hinds, 1999;](#page-8-0) [Wang and Christopher, 2003](#page-9-0)). Natural aerosol (dust and volcanic ash) and anthropogenic aerosol (smoke, urban haze, and industrial pollutants) may influence the energy budget of the earth-atmosphere 40

system, evaporation and cloud formation, precipitation patterns, and cause changes in regional and global climate [\(Kaufman et al., 2002\)](#page-9-0). 45

The issue took a turn for the better after Shanghai won the bid to host the World Expo 2010. The Shanghai

municipal government identified the air quality as a major component of environmental initiatives. Since then, the city has implemented comprehensive actions focused on the energy, industry, transport, and construction sectors for reduction of air pollution ([UNEP, 2010](#page-9-0)). By 2007, the proportion of coal used as a primary energy source in 50

Shanghai had dropped to 51.3% from 65% in 2000 [\(UNEP,](#page-9-0) 55

[2010](#page-9-0)). The use of natural gas, imported electricity, and renewable energy had increased significantly. Factories that used to be scattered around the city were either closed down or concentrated into modern industrial zones ([UNEP,](#page-9-0) [2010](#page-9-0)). Meanwhile, the city supports projects aiming to detect and monitor air quality variability. Here we present monitoring results using the aerosol optical depth (AOD) data measured by the moderate resolution imaging spectrometer (MODIS) onboard US Terra satellites ([Kauf](#page-9-0)[man et al., 2002](#page-9-0); [Remer et al., 2005](#page-9-0); [Levy et al., 2007\)](#page-9-0) and the air pollution index measured by the Shanghai Environmental Monitoring Center (SEMC). The purpose is to obtain the variability trend of air quality in Shanghai in the recent decade, and assess the efficiency of environmental initiatives done by the Shanghai municipal government for reduction of air pollution before and after the World Expo 2010. 30 35  $40$ 

## 2 Data

### 2.1 AOD time series data

Visible band sensors onboard satellites are capable of monitoring aerosols, their distribution and transport patterns, with a large spatial coverage and reliable repeated measurements. The AOD is an important and commonly accepted aerosol index retrieved from satellite sensors ([Wang and Christopher, 2003](#page-9-0); [Hutchison et al., 2004,](#page-9-0)

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Fig. 2 Terra MODIS aerosol optical depth image at 02:38UTC on August 13, 2010, acquired at East China Normal University Satellite Ground Receiving Station. Shanghai City, the study area, is marked as a bold circle. The AOD color codes are shown on the right. The black area shows no data.

[2005; Levy et al., 2007; Levy et al., 2009](#page-9-0); [Wang et al.,](#page-9-0) [2010\)](#page-9-0). MODIS-derived aerosol optical depth data have been validated with sunphotometer CE318 measurements over Yangtze River Delta in China. The evaluation results indicate that MODIS AODs are in good agreement with CE318 [\(He et al., 2010\)](#page-8-0). The data measured by the MODIS onboard US Terra and Aqua satellites provide an unprecedented opportunity to monitor aerosols in the atmosphere and examine the role of aerosols in the earthatmosphere system ([Kaufman et al., 2002\)](#page-9-0).

In this study, AOD time series data derived from Terra MODIS measurements are used. We use 12 years of MODIS AOD level 2 daily products from 2000 to 2011 for detailed variability trend analysis of urban and suburban districts of Shanghai. The archived data from March 2000 to June 2010 are downloaded from Collection 5 of US NASA Goddard Space Flight Center<sup>1</sup>. The data from July 2010 to October 2011 were received and processed by the East China Normal University Satellite Ground Receiving Station. The AOD retrieval algorithm, which is used by the East China Normal University Satellite Ground Receiving Station, is the same as the one used for retrieving aerosol products in Collection 5. Fig. 2 shows an example of AOD images computed with Terra MODIS data on August 13, 2010, and received by East China Normal University Satellite Ground Receiving Station. One can see that the data points are not uniformly distributed due to the cloud contamination. Thus averaging is always needed to 40 45 50

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construct a continuous time series data set. Thus we average MODIS AOD level 2 daily products to obtain the AOD data with a temporal resolution of one month. 1

### 2.2 API time series data

The API is used as a measure to classify air quality to the public in a simple and generalized way in China. The API values are integer values, which are obtained by converting monitored daily average air quality data. In Shanghai, the SEMC is responsible for monitoring the indicator pollutants every hour, which are respirable particulate matter (PM<sub>10</sub>), SO<sub>2</sub>, and nitrogen dioxide (NO<sub>2</sub>), converting them to API values, and reporting the API to the public. An individual score of the three indicator pollutants is 15 assigned to the level of each pollutant according to the designed breakpoints listed in Table 1. The final API is the highest of the three scores. 10

The daily average API data used in this study were measured at seven automatic monitoring stations under 20 SEMC: Stations Hongkou, Yangpu, Putuo, Jing'an, Pudong, Xuhui, and Qingpu as shown in Fig. 3. Except Qingpu station that is located in suburban area, the other six stations are located in the downtown area of Shanghai. In these stations,  $PM_{10}$  is measured by a Rupprecht & Patashnick TEOM 1400a. Gaseous pollutants  $SO_2$  and  $NO<sub>2</sub>$  are monitored by a Teledyne Advanced Pollution Instrumentation UV Fluorescence Analyzer 100E (TAPI) and a Chemiluminescence Analyzer 200E (Jiang et al., 2004). The API time series data from January 2006 to 30 October 2011 are used for the analysis and comparison with MODIS AOD time series. 25

### 3 Ensemble empirical mode decomposition (EEMD) method

We use the EEMD method to analyze the AOD and API time series data in Shanghai [\(Wu and Huang, 2009](#page-9-0)). The 40 purposes are (i) to determine the variability trend of air quality in the recent decade, (ii) to determine the intrinsic components of different time scales that have contribution to the fluctuation of AOD and API, (iii) to diagnose the behavior of each component during the World Expo 2010, 45 and (iv) to obtain the variability trends of AOD and API.

Empirical mode decomposition (EMD), which can be applied to nonlinear and non-stationary processes, is a new time-frequency analysis technique [\(Huang et al., 1998\)](#page-8-0). The EEMD method is an accuracy-improved version of the 50 EMD. It can eliminate the mode mixing problem which exists in the EMD in all cases [\(Wu and Huang, 2009\)](#page-9-0). The EMD method is empirical because the local characteristic time scales of the data are used to decompose the time

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<sup>1)</sup> http://ladsweb.nascom.nasa.gov/data/

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Table 1 Breakpoints of APIs and Health Implications (partially referred to Jiang et al., (2004))

	Air quality class	API	Air Pollution Level	Health Implication	$SO_2/(mg \cdot m^{-3})$		$NO_2/(mg \cdot m^{-3})$ $PM_{10}/(mg \cdot m^{-3})$
		$0 - 50$	Excellent	No health implications	$0.000 - 0.050$	$0.000 - 0.080$	$0.000 - 0.050$
		$50 - 100$	Good	No health implications	$0.050 - 0.150$	$0.080 - 0.120$	$0.050 - 0.150$
	IΙI	$100 - 200$	Lightly Polluted	Slight irritations may occur	$0.150 - 0.800$	$0.120 - 0.280$	$0.150 - 0.350$
	IV	$200 - 300$	Moderately Pol- luted	Healthy people will be noticeably affected.	$0.800 - 1.600$	$0.280 - 0.565$	$0.350 - 0.425$
10 <sup>1</sup>	V	$300 - 400$	<b>Heavily Polluted</b>	Healthy people will be noticeably affected.	$1.600 - 2.100$	$0.565 - 0.750$	$0.420 - 0.500$
		$400 - 500$		Healthy people will experience reduced endurance in activities.	$2.100 - 2.620$	$0.750 - 0.940$	$0.500 - 0.600$



Fig. 3 API monitoring stations used in this study. Black triangle represents the center of downtown of Shanghai that is used as a reference point to measure the distance to each API monitoring station.

series. The key part of this method is that any complicated data set can be decomposed into a finite and often small number of intrinsic mode functions (IMFs). These IMFs, which are determined by the signal itself and not predetermined kernels, represent the natural oscillatory mode embedded in a signal. After removing all IMFs from the data set, the remaining data represent the local trend for the 40

observation period. Mathematically, this procedure can be expressed as follows [\(Huang et al., 1998](#page-8-0)). A time series data set  $x(t)$  is decomposed in terms of IMFs,  $c_i$ , i.e., 45

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x(t) = \sum_{j=1}^{n} c_j + r_n
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where  $r_n$  is the trend or residue. IMFs are simple oscillatory functions with varying amplitude and frequency. The structure of each IMF is determined by the natural amplitude variations in the time series. Higher frequency oscillations are captured in the first IMF and subsequent IMFs have lower frequencies. The EEMD method can reduce the influences caused by different frequencies and therefore obtain a more realistic trend (see Fig. 4) than the result directly derived from a traditional linear regression method ([Huang et al., 1998;](#page-8-0) [Wu and Huang, 2009](#page-9-0)).

## 4 Variability of AOD in Shanghai

For the AOD variability analysis with an emphasis on the World Expo 2010 period, we use 11 years of MODIS AOD time series data of the Shanghai urban area from March 2000 to January 2011 as shown in Fig. 4. To examine the time scales of AOD variability in Shanghai, we decomposed the time series data into intrinsic components with the EEMD method. The results are shown in Fig. 5. The data set and a trend or residue are shown as a dash-dot line in Fig. 4. IMF C1 represents the seasonal fluctuation signal. IMF C2 represents an annual signal. IMF C3 also represents an annual signal but with different phases from C2. IMF C4 represents a biannual signal. IMF C5 represents an inter-annual signal.



Fig. 4 Monthly AOD data in Shanghai from March 2000 to January 2011 derived from Terra MODIS observations (solid line). Dash-dot line represents a long-term variability trend of the data set derived from the EEMD analysis.

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#### 4.1 IMF amplitude analysis

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From the trend shown in Fig. 4 and the IMFs in Fig. 5, The amplitude of the trend is near 1.0, the peak-to-peak amplitudes of C1 and C3 are  $O(\pm 0.25)$ , that of C2 is  $O(\pm 0.30)$  and that of C4 and C5 is  $O(\pm 0.05)$ . The peak-topeak amplitude of  $C2 + C3$  (not shown) is  $O(\pm 0.50)$ . This implies that the trend represents a dominant component of long-term variability of 11 years of AOD in Shanghai. The annual variability (IMFs C2 and C3) is a dominant component for the fluctuation of AOD. The seasonal variability (IMF C1) is not a dominant component, but large enough. The biannual (IMF C4) and the inter-annual (IMF C5) components are relatively small and negligible. 1

4.2 Behavior of IMFs during the World Expo 2010

From the monthly AOD data in Shanghai shown in Fig. 4, we calculate the average AOD level in whole year of 2010 as 0.70, which is 30% less in comparison to the long-term trend. The maximum fluctuation peak of 1.03 occurred in June 2010, which is 45% less in comparison to that in the previous year 2009. The seasonal component IMF C1 did not show remarkable change in 2010. The positive halfamplitude of annual component IMF C2 decreased 80% in comparison to the last ten-year average value shown as the 5 10



Fig. 5 IMFs C1–C5 derived from 11 years of monthly AOD data of Shanghai from March 2000 to January 2011. The black dashed curve is the last ten-year average value. 55

- black dashed curve. The positive half-amplitude of IMF C3 completely disappeared, i.e., a 100% decrease. The biannual component IMF C4 appeared as a quite small value  $[O(\pm 0.05)]$  before 2010, but in 2010 showed a 1
- remarkable drop of the negative half-amplitude, about 3.5 times the last ten-year average value as shown by the red dashed curve. These results indicate that all the dominant components of AOD variability in Shanghai were reduced during the World Expo 2010. In other words, from the 5
- point of view of AOD, the air quality was remarkably improved in Shanghai during the World Expo 2010 compared to previous years. 10

#### 5 Variability trend analysis of urban and suburban districts 15

### 5.1 EEMD analysis results

- As mentioned in Sections 2.1 and 2.2, we use 12 years of MODIS AOD level 2 daily products from March 2000 to October 2011 and six years of API daily data from January 2006 to October 2011 for detailed variability trend analysis of selected urban and suburban districts of Shanghai. 20
- Again, the EEMD method is used to analyze the time series data of all the stations. As an example, Fig. 6 shows the EEMD analysis results of AOD for the Xuhui District, which is located in the downtown area of Shanghai. The AOD time series data shown on top are decomposed into 25
- six IMFs C1–C6 and a trend. IMF C1 represents a monthly fluctuation signal. IMF C2 represents a semi-annual signal. IMF C3 represents an annual signal. IMF C4 represents a 30

biannual signal. IMFs C5 and C6 represent inter-annual signals. Among the six IMFs, the first three components, i.e., monthly, semi-annual, and annual signals, have much larger amplitudes compared to the other three, implying that they are dominant components of AOD variability in the Xuhui District. This implies that the monsoon weather is a dominant factor in modulating the AOD variability in Shanghai. The other districts manifest similar results (not shown).

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 $Fi \implies$  7 shows the EEMD analysis results of API for the Xuhu $\overline{\nu}$ District. One can see that the API time series data shown on top are de-composited into five IMFs C1–C5 and a trend. IMF C1 represents a semi-annual signal. IMFs C2 and C3 represent annual signals with different phases. IMFs C4 and C5 represent inter-annual signals. Among the five IMFs, the first three components, i.e., the semi-annual and the two annual signals, have much larger amplitudes compared to other two, implying that they are dominant components of API variability in the Xuhui District. Again, this implies that the monsoon weather is a dominant factor in modulating the API variability in Shanghai. Compared to AOD components, however, the API variability misses a high frequency component, the monthly signal, implying that the API is not as active as the AOD. The other districts manifest similar results (not shown). 10 15 20 25

### 5.2 Variability trend analysis of AOD

Compared to the IMFs described in the above section, the trends are more important for assessment of the air quality variability and evaluation of environmental policy perfor-30

 $C<sub>1</sub>$ 

 $C2$ 

 $C<sub>3</sub>$ 

C4



 $0.5$  $\Omega$ 

 $-0.5$  $0.2$  $\Omega$ 

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Fig. 7 Daily API data of Xuhui District of Shanghai observed by Shanghai Environmental Monitoring Center (SEMC) from January 2006 to October 2011 (top) and decomposed IMFs C1–C5. Dash-dot line represents a long-term variability trend.



Fig. 8 Variability trends of AOD in selected districts of Shanghai from 2000 to 2011. Curves in different colors represent the cases of different districts listed on top right. Note that Districts Hongkou and Yangpu share the pink curve, and Xuhui, Jing'an and Putuo the light blue one. Red curve represents the average of top three curves.

mance. Fig. 8 shows variability trends of AOD in selected districts of Shanghai from 2000 to 2011 derived from the EEMD analysis. The curves can be divided into two groups. The top three represent six districts, Hongkou, Yangpu, Pudong, Xuhui, Jing'an, and Putuo, which are located in the downtown area of Shanghai, and lower one represents District Qingpu, which is located in the most 50 55

western suburban of Shanghai (see Fig. 3). All the curves show similar trends, i.e., from 2000 the AOD started a monotonic increase, reached the maxima around 2006 (2005 for Qingpu and 2007 for Pudong), then monotonically decreased till 2011. This result indicates that from the point of view of AOD, the air quality in the entire Shanghai area, no matter whether urban or suburban areas, 50 55



Fig. 9 Variability trends of API in selected districts of Shanghai from 2006 to 2011

has been remarkably improved since around 2006. In addition, the average of the top three curves is about 8% higher than the lower one. In other words, the AOD in the downtown areas has a relatively high level in comparison to the far suburban areas. This difference seems to reveal that pollution induced by human activities constitute an important source for AOD in Shanghai. 25

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5.3 Variability trend analysis of API

Fig. 9 shows variability trends of API in selected districts of Shanghai from 2006 to 2011 derived from EEMD analysis. One can see that unlike the case of AOD, the curves cannot be divided into groups, but all the curves show a similar trend, i.e., from around 2006 (2007 for Xuhui and 2008 for Jing'an) the API started to decrease till 2011. This result indicates that from the point of view of API, the air quality in the entire Shanghai area, no matter 35 40

- whether urban or suburban areas, has also remarkably been improved since around 2006.
- 5.4 Regional distribution of air quality improvement 45

The variability trends of AOD and API in the recent decade obtained in Sections 5.2 and 5.3 indicate that the air quality in the entire Shanghai area has remarkably been improved since around 2006. From Figs. 8 and 9, however, one can

see that the improved degrees (IDS) in the selected districts are distinct. To quantitatively describe the IDS of air quality in the selected districts, we calculate the relative decrease (percentage) of AOD and API from their maxima occurring around 2006 to their values in 2011; the results 50 55

are shown in Fig. 10. One can see that the mean and the

standard deviation of AOD IDS in all the selected districts are  $(8.6\pm1.9)\%$ , implying a near uniform distribution of AOD IDS. On the other hand, API IDS shows greater differences with a mean and standard deviation of  $(9.2\pm7.1)\%$ , ranging from a minimum value of 1.5% in Putuo District to a maximum value of 22% in Xuhui District. However, from Fig. 10, one can see that there is a general trend in spatial distribution of API IDS, i.e., the districts of further distance from the reference point (center of downtown) show higher API IDS.

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Fig. 10 Improved degrees (IDS) of AOD and API in the selected districts of Shanghai from 2006 to 2011

### 6 Discussion

From section 5, one can see that variability trends of API in selected districts of Shanghai from 2006 to 2011 derived from EEMD analysis are highly correlated to that of AOD. API is a parameter derived from a group of field-measured data as described in section 2.2. This implies that API represents a kind of field data. Highly correlated variability trends between API and AOD indicate an internal link between the two. Thus it is sound to use the trends derived from AOD as an alternate parameter to assess the longterm variability of air quality.

After this research has been done, a new version (Collection 5.1) of monthly mean AOD data are available on-line. To estimate potential impact of the new version of AOD data to the results of our research, we use exactly the same method to process the monthly AOD data in Shanghai from 2000 to 2012 in the new version. The results show that the long-term trend and IMF C1-C3 also are major components. The long-term trend value in 2010- 2011 reduced 13% in comparison to the peak value in 2007. The seasonal component IMF C1 did not show remarkable change in 2010-2011. The amplitude of annual component IMF C2 in 2010–2011 decreased 40% in comparison to that in 2009. The positive half-amplitude of

<span id="page-8-0"></span>IMF C3 decreased gradually from 2007 and completely disappeared in 2010, i.e., a 100% reduction. These results indicate that all the dominant components of AOD variability in Shanghai derived from the new version of AOD data show quite similar behavior during the World Expo 2010 to that derived from the monthly mean data we generated for this study as given in section 4. In other words, the results derived from the new version of AOD data in fact enhance the results and conclusions of this research. 1 5 10

### 7 Summary

This study uses US Terra satellite MODIS AOD data, API data, and the EEMD method to analyze the air quality variability in Shanghai in the recent decade and behavior of obtained IMFs during the World Expo 2010. The variability trends of selected urban and suburban districts of Shanghai are analyzed. The results indicate that the trend of amplitude near 1.0 is a dominant component of AOD long-term variability in Shanghai. The annual variability is a dominant component for AOD fluctuation. 15 20

During the World Expo 2010, the average AOD level was 0.70, which decreased 30% in comparison to the longterm trend. The maximum fluctuation peak decreased 45% in comparison to that in the previous year 2009. Two dominant annual components decreased 80% and 100%, respectively, in comparison to the last ten-year average value. This implies that the air quality in Shanghai was remarkably improved. The improved air quality demonstrates that environmental initiatives and comprehensive actions focused on reduction of air pollution, having been implemented by the Shanghai municipal government since wining to host the World Expo 2010 in 2002, are effective. 25 30 35

> The analysis results of AOD variability trends for selected districts in Shanghai indicate that monthly, semiannual, and annual signals are dominant components. The API time series data are also decomposed into five IMFs with the EEMD method. The semi-annual and annual signals are dominant components of API variability. This implies that the monsoon weather is a dominant factor in modulating the AOD and API variability in Shanghai.

The variability trends of AOD in selected districts, which are located in both downtown and suburban areas of Shanghai, show that from 2000 the AOD began a monotonic increase, reached the maxima around 2006 (2005 for Qingpu and 2007 for Pudong), then monotonically decreased till 2011. The variability trends of API show that from around 2006 (2007 for Xuhui and 2008 for Jing'an) the API started to decrease till 2011. This implies that the air quality in the entire Shanghai area, no matter whether urban or suburban areas, has remarkably improved since around 2006. In addition, the AOD in the downtown area has a relatively high level in comparison to the far suburban area. This difference 45 50 55

seems to reveal that pollution induced by human activities constitute an important source for the AOD in Shanghai. 1

To quantitatively describe the improved degrees of air quality in the selected districts, we calculate the relative decrease (percentage) of AOD and API from their maxima occuring around 2006 to their values in 2011. The mean and the standard deviation of AOD IDS in all the selected districts are  $(8.6\pm1.9)\%$ , implying a near uniform distribution of AOD IDS. On the other hand, API IDS show greater differences with a mean and standard 10 deviation of  $(9.2\pm7.1)\%$ , ranging from a minimum value of 1.5% in the Putuo District to a maximum value of 22% in the Xuhui District. There is a general trend in spatial distribution of API IDS, i.e., the districts of further distance from the center of downtown show higher API IDS. 5 15

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### References

- Chan C K, Yao X (2008). Air pollution in mega cities in China. Atmos Environ, 42(1): 1–42
- Chen B, Hong C, Kan H (2004). Exposures and health outcomes from  $30$ outdoor air pollutants in China. Toxicology, 198(1–3): 291–300

Chen C H, Wang B Y, Fu Q Y, Green C, Streets D G (2006). Reductions in emissions of local air pollutants and co-benefits of Chinese energy policy: a Shanghai case study. Energy Policy, 34(6): 754–762

- Hao N, Valks P, Loyola D, Cheng Y F, Zimmer W (2011). Space-based measurements of air quality during the World Expo 2010 in Shanghai. Environ Res Lett, 6(4): 1–9 35
- He Q, Li C, Tang X, Li H, Geng F, Wu Y (2010). Validation of MODIS derived aerosol optical depth over the Yangtze River Delta in China. Remote Sens Environ, 114(8): 1649–1661
- Hinds W C (1999). Aerosol Technology Properties, Behavior, and Measurement of Airborne Particles. 2nd ed. New York: Wiley-Interscience, 504
- Huang N E, Shen Z, Long S R, Wu M C, Shih E H, Zheng Q, Tung C C, Liu H H (1998). The Empirical mode decomposition method and the  $45$ Hilbert spectrum for non-stationary time series analysis. Proceedings of Royal Society London, 454(1971): 903–995
- Huang W, Tan J, Kan H, Zhao N, Song W, Song G, Chen G, Jiang L, Jiang C, Chen R, Chen B (2009). Visibility, air quality and daily mortality in Shanghai, China. Sci Total Environ, 407(10): 3295–3300 50
- Jiang D, Zhang Y, Hu X, Zeng Y, Tan J, Shao D (2004). Progress in developing an ANN model for air pollution index forecast. Atmos Environ, 38(40): 7055–7064

Kan H, Chen B (2003a). A case-crossover analysis of air pollution and daily mortality in Shanghai. J Occup Health, 45(2): 119–124

Kan H, Chen B (2003b). Air pollution and daily mortality in Shanghai: a

40

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40

<span id="page-9-0"></span>time-series study. Arch Environ Health, 58(6): 360–367 1

- Kan H, Chen B (2004). Particulate air pollution in urban areas of Shanghai, China: health-based economic assessment. Sci Total Environ, 322(1–3): 71–79
- Kan H, London S J, Chen G, Zhang Y, Song G, Zhao N, Jiang L, Chen B (2007). Differentiating the effects of fine and coarse particles on daily mortality in Shanghai, China. Environ Int, 33(3): 376–384 5
- Kaufman Y J, Tanré D, Boucher O (2002). A satellite view of aerosols in the climate system. Nature, 419(6903): 215–223
- Hutchison K D, Smith S, Faruqui S (2004). The use of MODIS data and aerosol products for air quality prediction. Atmos Environ, 38(30): 5057–5070 10
	- Hutchison K D, Smith S, Faruqui S (2005). Correlation MODIS aerosol optical thickness data with ground-base PM2.5 observations across
- Texas for use in a real-time air quality prediction system. Atmos Environ, 39(37): 7190–7203 15

Levy R C, Leptoukh G G, Kahn R, Zubko V, Gopalan A, Remer L A (2009). A critical look at deriving monthly aerosol optical depth from satellite data. IEEE Trans Geosci Rem Sens, 47(8): 2942–2956

Levy R C, Remer L A, Mattoo S, Vermote E F, Kaufman Y J (2007). 20 Second-generation operation algorithm: retrieval of aerosol properties over land from inversion of moderate resolution imaging spectroradiometer spectral reflectance. J Geophys Res, 112(D13): 1–21

Mage D, Ozolins G, Peterson P, Webster A, Orthofer R, Vandeweerd V, Gwynne M (1996). Urban air pollution in megacities of the world. Atmos Environ, 30(5): 681–686 25

Remer L A, Kaufman Y J, Tanre D, Mattoo S, Chu D A, Martins J V, Li R R, Ichoku C, Levy R C, Kleidman R G, Eck T F, Vermote E, Holben B N (2005). The MODIS aerosol algorithm products and validation. J Atmos Sci, 62(4): 947–973

- UNEP (United Nations Environment Programme) (2010), UNEP Environmental Assessment, EXPO 2010, Shanghai, China, 1–147.
- Wang J, Christopher S A (2003). Intercomparison between satellitederived aerosol optical thickness and PM<sub>2.5</sub> mass: Implications for air quality studies. Geophys Res Lett, 30(2095): 1–4
- Wang J, Xu X, Spurr R, Wang Y, Drury E (2010). Improved algorithm for MODIS satellite retrievals of aerosol optical thickness over land in dusty atmosphere: implications for air quality monitoring in China. Remote Sens Environ, 114(11): 2575–2583
- Wang Y, Zhuang G, Zhang X, Huang K, Xu C, Tang A, Cheng J, An Z (2006). The ion chemistry, seasonal cycle, and sources of  $PM_{2.5}$  and TSP aerosol in Shanghai. Atmos Environ, 40(16): 2935–2952
- World Health Organization (WHO) (1987). Air Quality Guidelines for Europe. WHO Regional Publications, European Series No. 23, WHO Regional Office for Europe, Copenhagen.

World Health Organization/United Nations Environment Programme (WHO/UNEP) (1992). Urban Air Pollution in Megacities of the World. Oxford: Blackwell.

- World Health Organization/United Nations Environment Programme (WHO/UNEP) (1994). Air Pollution in the World'S Megacities Environment, 36: 4–37
- Wu Z, Huang N E (2009). Ensemble empirical mode decomposition: a noise-assisted data analysis method. Advances in Adaptive Data Analysis, 1(1): 1–41
- Zhang Y H, Huang W, London S J, Song G X, Chen G H, Jiang L L, Zhao N Q, Chen B H, Kan H D (2006). Ozone and daily mortality in Shanghai, China. Environ Health Perspect, 114(8): 1227–1232

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